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ScienceDirect
Journal of Financial Markets 12 (2009) 438–468
Journal of FINANCIAL MARKETS
www.elsevier.com/locate/finmar

Idiosyncratic risk and the cross-section of stock returns: Merton (1987) meets Miller (1977)

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Available online 1 February 2009

Abstract

Merton [1987. A simple model of capital market equilibrium with incomplete information. Journal of Finance 42, 483–510] predicts that idiosyncratic risk should be priced when investors hold sub-optimally diversified portfolios, and cross-sectional stock returns should be positively related to their idiosyncratic risk. However, the literature generally finds a *negative* relationship between returns and idiosyncratic risk, which is more consistent with Miller's [1977. Risk, uncertainty, and divergence of opinion. Journal of Finance 32, 1151–1168] analysis of asset pricing under short-sale constraints. We examine the cross-sectional effects of idiosyncratic risk while explicitly recognizing the confounding effects that dispersion of beliefs and short-sale constraints produce in the Merton framework. We find strong support for Merton's [1987. A simple model of capital market equilibrium with incomplete information. Journal of Finance 42, 483–510] model among stocks that have low levels of investor recognition and for which short selling is limited. For these stocks, the relation between idiosyncratic risk and expected returns is positive, as predicted by Merton [1987. A simple model of capital market equilibrium with incomplete information. Journal of Finance 42, 483–510].

JEL classification: G10; G12; G14

Keywords: Market efficiency; Idiosyncratic risk; Short sales

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doi:10.1016/j.finmar.2009.01.004

According to the textbook capital asset pricing model (CAPM), idiosyncratic risk is not priced because investors hold efficiently diversified portfolios. However, the model makes no predictions concerning the effect of idiosyncratic risk on equilibrium returns if investors are constrained from forming diversified portfolios because of transactions costs (e.g., information or trading costs).

In an influential paper, Merton (1987) presents an extension of the CAPM where idiosyncratic risk plays a role in equilibrium. Merton forwards the investor recognition hypothesis (IRH), which posits that, because of incomplete information on security characteristics, investors only hold securities whose risk and returns characteristics they are familiar with. Consequently, they hold under-diversified portfolios and, in the static mean-variance setting considered by Merton, they demand compensation for securities' idiosyncratic risk.[1] Thus, in equilibrium, cross-sectional stock returns are positively related to their idiosyncratic risk.[2]

Direct tests of Merton's (1987) model are rare. Merton's predictions are cross-sectional in nature, but Ang et al. (2006) appears to be the only cross-sectional test of Merton (1987) that directly sorts stocks into portfolios ranked on idiosyncratic volatility. Observing that stocks with high idiosyncratic volatility have "abysmally low average returns," they conclude their results are directly opposite to the implications of Merton's (static) IRH.

Meanwhile, Diether et al. (2002) offer an indirect test of Merton (1987). Since dispersion in analysts' forecasts likely indicates a more volatile, less predictable earnings stream, Diether et al. (2002) suggest that the dispersion of analysts' forecasts reflects the type of idiosyncratic risk to which Merton refers. Their results do not support Merton's theory, and they note "our results clearly reject the notion that dispersion can be viewed as a proxy for risk, since the relation between dispersion and future returns is strongly negative," (p. 2139). Similarly, when Gebhardt et al. (2001) use forecast dispersion as a risk proxy for estimating cost of capital, they are surprised to find the "wrong sign" on the variable at statistically and economically significant levels.

Thus, both in direct tests using idiosyncratic volatility as a proxy for idiosyncratic risk, and in indirect tests that use analysts' forecast dispersion as a risk proxy, cross-sectional results are incorrectly signed, compared to Merton's (1987) predictions, at high levels of statistical significance. Based on the empirical tests to date, the literature concludes that Merton's hypothesis, while both intuitively appealing and theoretically well grounded, is not supported by the data. Instead, Diether et al. (2002) argue that their results, along with those of Gebhardt et al. (2001), are more consistent with predictions of Miller (1977).

Miller (1977) argues that dispersion of opinion, in the presence of short-sale constraints, leads to systematic security overvaluation because the most optimistic market participants set a stock's price. Thus, dispersion of investor opinion is priced at a *premium* when short-sale constraints are present. Miller's theory implies that *if* short-sale constraints are

[1]Mayers (1976) and Levy (1978) produce similar predictions in CAPM extensions where investors hold under-diversified portfolios. Barberis and Huang (2001) produce a prospect-theory model where idiosyncratic risk produces positive expected returns.

[2]Shapiro (2002) generalizes the IRH to a dynamic setting and shows that this conclusion need not hold when the investment opportunity set is stochastically evolving, since higher volatility stocks may still provide a more effective hedge against shifting investment opportunities, compared to lower volatility stocks.

binding, there is a negative correlation between risk-adjusted returns and dispersion of beliefs.[3]

Diether et al. (2002) interpret the observed negative correlation between returns and analyst forecast dispersion as supportive of Miller (1977), but contrary to the predictions of Merton (1987), because the dispersion of analysts' forecasts and idiosyncratic volatility are positively correlated. For example, Peterson and Peterson (1982) observe a positive relationship between return volatility and the dispersion of I/B/E/S forecasts.

However, there are strong reasons to question whether Merton (1987) should be viewed as a competing theory to Miller (1977). While Miller assumes that stocks are short-sale constrained, Merton models a standard frictionless market, without borrowing and short-selling restrictions (see, p. 487). While Merton's IRH applies to low-visibility securities, Miller makes no low-visibility assumption.

We hypothesize that the previous tests of Merton (1987) fail to find that idiosyncratic risk is priced for two reasons. First, Merton's hypothesis applies only to stocks with low visibility, but the existing literature does not condition on visibility. Second, none of the existing studies condition on the level of short interest. Conditioning on short interest is important because short interest is indicative of both dispersion of investor opinion and potential difficulty in shorting. Miller (1977) contends that these conditions are prerequisite for overvaluation. Since dispersion of beliefs has been empirically demonstrated to be positively correlated with idiosyncratic risk, Miller-style dispersion-of-opinion induced overvaluation might obscure evidence of Merton's IRH among more highly shorted stocks.

It is also possible that negative abnormal returns that follow high observed short interest *are not* driven by Miller-style overvaluation arising from short-sale constraints. Instead, high short interest may simply reflect a temporary overvaluation that has been identified by "smart" short sellers who have received negative information ahead of the other investors and sold short in response to negative news not yet reflected in market prices. Either way, numerous studies report that stocks with high levels of short interest are followed by negative abnormal returns.[4] The impact on tests of Merton's IRH is the same irrespective of the mechanism that links short interest to overvaluation. Heavily shorted firms are likely to underperform their benchmarks, and excluding them should prove helpful in detecting evidence supportive of Merton's IRH in the remaining sample. Thus, we propose to exclude stocks with high levels of short interest and focus appropriate tests of Merton (1987) on those stocks that are not heavily shorted.

Because Merton's model applies to stocks with low visibility, in the sense that some investors are unaware of the firm's risk-return parameters, we expect to find empirical support for Merton's IRH only among low-visibility stocks, and more specifically within a subset of low-visibility stocks that are not subject to significant levels of short selling. Accordingly, we analyze the cross-sectional relation between idiosyncratic risk and equity returns for low-visibility firms while controlling for short-sale activity.

[3]Indeed, several other theoretical papers derive similar asset pricing predictions. A non-exhaustive set includes Figlewski (1981), Morris (1996), Viswanathan (2002), Chen et al. (2002), Danielsen and Sorescu (2001), and Duffie et al. (2002). In contrast, Jarrow (1980) and Diamond and Verrecchia (1987) provide alternative theories of the effects of short-sale constraints on security prices.

[4]For example, see Figlewski (1981), Asquith and Meulbroek (1995), Danielsen and Sorescu (2001), Desai et al. (2002), Asquith et al. (2005), and Boehme et al. (2006).

Falkenstein (1996) and Aggarwal et al. (2005) link institutional ownership (IO) (positively) to firm visibility. We utilize this relationship and screen out firms with high levels of IO (high-visibility) for whom the IRH should not apply. Using data on short interest on NYSE and NASDAQ stocks from 1988 to 2002 and IO data for the same period, we find that cross-sectional returns are positively correlated with idiosyncratic volatility, as predicted by Merton (1987), for less visible stocks that are not subject to significant short selling. For completeness, we also examine the cross-section of volatility for stocks that have greater visibility and/or greater shorting activity. We do not find the positive correlation between volatility and ex post returns for those firms.

We conduct similar tests using I/B/E/S sell-side analyst coverage as a proxy for visibility. Aggarwal et al. (2005) note that firms that lack analyst coverage are presumed to lack visibility. Baker et al. (1999) also use analyst coverage as a visibility proxy in testing the impact of NYSE listing on firm visibility. Again, we find that cross-sectional returns are positively correlated with idiosyncratic volatility for firms that lack analyst coverage and do not exhibit significant short selling activity.

Finally, we conduct a series of cross-sectional Fama–MacBeth (1973) regressions on monthly returns of various portfolios constructed to isolate the impact of volatility in the presence of low visibility and low short selling activities. Again, the results are supportive of Merton's (1987) hypothesis. Among other advantages, the Fama–MacBeth method allows for easy incorporation of risk factors and control variables into the cross-sectional regression analysis.

We organize the rest of this paper as follows. Section 1 develops the testable hypotheses and discusses our testing methodology and empirical proxies. Section 2 presents base-line cross-sectional effects. Section 3 presents empirical tests of Merton (1987) using IO as a proxy for visibility, and Section 4 repeats the analysis for firms lacking financial analyst coverage. Section 5 documents further evidence in support of the hypothesis using cross-sectional tests in a Fama–MacBeth framework, and Section 6 summarizes and concludes.

1. Hypotheses, explanatory variables, and test design

Based on the foregoing analysis, we hypothesize that cross-sectional differences in idiosyncratic volatility are positively correlated with subsequent returns when firms have low visibility and low dispersion of beliefs, the latter condition being proxied by low short interest. For more heavily shorted firms, the relationship between idiosyncratic risk and returns is potentially obscure because of the positive correlation between dispersion of beliefs and idiosyncratic risk. In fact, if the countervailing influence of dispersion of beliefs is particularly strong, heavily shorted firms may display a negative correlation between idiosyncratic risk and returns.

We now describe the independent (or explanatory) variables used in the analysis, as well as our methodology for measuring stock returns.

1.1. Visibility metrics

The Merton (1987) model applies to stocks with low visibility. That is, the IRH applies to stocks for which some segment of investors is unaware of all the relevant risk-return tradeoff parameters.

We use two proxies for visibility. The first is IO. Falkenstein (1996) finds that institutional investors (specifically U.S. mutual funds) have a significant preference for stocks with high visibility, as measured by coverage in newspaper articles. Similarly, Aggarwal et al. (2005) find that IO is positively correlated with visibility, as proxied by the number of analysts following the stock.

We calculate *IO* as the ratio of the total or aggregate number of shares held by institutions (13F filings) to the total number of shares outstanding reported by CRSP for the end of the calendar month of the 13F filing. The 13F records provide institutional holdings on a quarterly basis. Therefore, we use the *IO* for the month in which the 13F's are filed and for the subsequent two months. For example, if a firm had 40% IO at the end of March 1996, we use that 40% ownership percentage estimate also for April and May.[5]

Our second proxy for visibility is the presence of analyst coverage. This proxy follows Aggarwal et al. (2005), who observe that analyst following is one ''of the strongest determinants of U.S fund investment decisions,'' (p. 2937). Firms lacking analyst coverage in Thompson Financial's I/B/E/S database are deemed to have low visibility. These represent a large fraction of all CRSP firms: over 50% in 1988 and over 36% in 2003, at the end of our study period.

1.2. Short-sale demand

Asquith et al. (2005) proxy for a limited supply of lendable shares using *IO*, and they proxy for short-sale demand (i.e., dispersion of opinion) using short interest levels, or ''*relative short interest*'' (*RSI*). They find negative abnormal returns for low-*IO*, high-*RSI* stocks, which they interpret as consistent with Miller (1977). They find no evidence of negative abnormal returns for all other stocks.

The Asquith et al. (2005) argument suggests that the Miller hypothesis should apply *only* to firms with low *IO* and high *RSI*. Hence, Miller-style overpricing should not apply to all other firms, i.e., those not subject to low *IO* and high *RSI*. And while Merton's IRH should apply whenever firm visibility is low, it should be most easily detected when the *RSI* does not produce confounding effects. Thus, Merton's IRH should be most easily observed where firms have low visibility (low *IO*) *and* low dispersion of opinion (low *RSI*).

We obtain short interest data from the New York Stock Exchange and the NASDAQ. Consistent with Asquith et al. (2005), we divide short interest by shares outstanding to calculate the *RSI*. Our sample is composed of all firms for which short interest data are electronically available from these sources. For both NYSE and NASDAQ firms, such data are available beginning with January of 1988. We collect all short interest data on a monthly basis for transactions settling by the 15th of each month. We use the ticker symbols shown in the short interest reports to match each observation with CRSP data.[6]

[5]Institutional ownership data is missing for some firms in the Thompson Financial database. Most of these missing firms probably have no institutional ownership. However, some omissions are simple errors. For example, a data error seems likely when a firm is covered by 14 analysts but has no reported institutional ownership. We assume that firms with missing institutional ownership data have no institutional ownership in all of the tests reported in the tables. However, excluding missing observations, rather than recoding them as zero values, does not alter any of the substantive results.

[6]We noticed short interest data are occasionally missing for firms with valid CRSP data. We do not include such observations in our sample because we are unable to determine if they represent a zero level of short interest, or if short interest data are missing.

1.3. Measuring idiosyncratic risk (*SIGMA*)

We measure the idiosyncratic risk (*SIGMA*) as the standard deviation of weekly excess raw returns (firm return minus CRSP VWRETD index), estimated over the 52 weeks (the ending of the week is defined as of closing on Wednesdays) preceding the first day of each month. We perform this estimation method, as opposed to measuring idiosyncratic risk relative to the Fama/French (1993) and Carhart (1997) four-factor model, because illiquid stocks that are only slightly correlated with the four factors may result in spurious measures of high volatility as a result of asynchronous trading. However, in later tests we observe that our results are robust to the choice of the idiosyncratic risk metric.

1.4. Measuring subsequent stock returns

Stock returns are obtained from CRSP, and we adopt the standard four-factor, calendar-time portfolio approach for measuring abnormal returns. At the end of June in each year from 1988 to 2002 we use our explanatory variables to classify firms into portfolios. Firms with similar values on each dimension are grouped into equally weighted portfolios. For each portfolio, we first calculate the monthly raw returns during the 12-month period *subsequent* to the portfolio formation. In other words, the portfolios are constructed on ex ante information, and the returns are computed ex post. In a sense, the tests are conducted "out of sample," as in Spiegel and Wang (2005). Specifically, for each portfolio, we estimate the following four-factor regression model:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t}, \tag{1}$$

where $R_{p,t}$ represents the raw returns of each portfolio, and $R_{f,t}$ is the return of the one-month Treasury Bill. The four independent variables are the excess return on the market portfolio ($R_{m,t}$–$R_{f,t}$); the difference between the returns of value-weighted portfolios of small and big firm stocks (SMB_t); the difference in returns of value-weighted portfolios of high and low book-to-market stocks (HML_t); and, the difference in returns of value-weighted portfolios of firms with high and low prior momentum (UMD_t, or "up" minus "down"). Fama and French (1993) propose the first three factors, while Carhart (1997) proposes the momentum factor. Using the OLS estimation method, we interpret the intercept, α_p, from Eq. (1) as the mean monthly abnormal return of the calendar-time portfolio.[7]

Our most important tests compare returns between the calendar-time portfolios of stocks having different levels of volatility (*SIGMA*). As in Mitchell and Stafford (2000) and Boehme and Sorescu (2002), we perform these tests by constructing zero-investment portfolios with long positions in stocks having a certain mix of characteristics (such as low *IO*, low *RSI*, and high *SIGMA*) and short positions in stocks with a different mix (such as low *IO*, low *RSI*, and low *SIGMA*). These portfolios are referred to as long-short portfolios. This example is typical in that only the *SIGMA* variable is altered between the long and short legs of the portfolio. Thus, we can observe the marginal effect of *SIGMA* holding the other variables constant. The long-short portfolio returns are regressed on

[7]Results throughout the paper also hold using weighted least squares.

the four factors:

$$R_{high-SIGMA,t} - R_{low-SIGMA,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t}. \quad (2)$$

The intercept obtained in this manner (α_p) represents a measure of the relative abnormal performance of the high-*SIGMA* portfolio vis-à-vis the shorted low *SIGMA* portfolio.

In addition to calculating long-short portfolio abnormal returns under the four-factor model, for robustness we consider several alternative pricing model specifications. These include the CAPM, the Fama–French three-factor model, a simple raw-return model, and a five-factor model that augments the four-factor model with a liquidity factor. The liquidity factor deserves some additional comment, because it is relatively new to the literature.

Spiegel and Wang (2005) observe that firms with high idiosyncratic risk also have low liquidity, and thus high returns associated with increasing idiosyncratic risk may be due to the illiquidity premium rather than Merton's (1987) hypothesis.[8] We address this concern in robustness tests, where we control for aggregate liquidity risk by constructing a liquidity factor to augment the four-factor Fama/French and Carhart model. We build the liquidity factor using a procedure similar to the *LMH* (low minus high liquidity) factor estimation in Eckbo and Norli (2005); this estimation technique is similar in spirit to the *HML* Fama/French factor estimation procedure.

For each calendar month, we assign all NYSE, AMEX, and NASDAQ firms to two market capitalization portfolios (high or low), based on the median NYSE firm market capitalization for that month. Next, for each of these two market capitalization groupings, each month we sort the firms based on turnover (defined as average monthly shares traded divided by shares outstanding over the prior twelve months). For the calendar month following the portfolio formation, we estimate the returns to equally weighted portfolios of firms in the top and bottom 30% of prior 12-month turnover, for both the above and below NYSE median market capitalization groups. The low (high) liquidity portfolio is an equally weighted average of the two portfolios in the lowest (highest) 30% of turnover from the above and below median NYSE market capitalization firms. We calculate the *LMH* liquidity factor as the return to a zero investment portfolio holding a long position in the low liquidity portfolio and a short position in the high liquidity portfolio.

1.5. Descriptive statistics

Table 1 provides descriptive statistics for the proxy variables used. We provide a snapshot of firms in the dataset at five-year intervals beginning in 1988, the first year for which short interests data are available in digital form. Proxies are estimated for all U.S.-domiciled common stocks listed on the NYSE and NASDAQ.

Both *IO* and *RSI* increased substantially between 1988 and 2002. However, no clear trend in *SIGMA* is noticeable. Because we form portfolios based on rank-orderings of each of these variables, neither a small number of extreme values, nor the non-stationarity in the time series of a variable introduces any bias to the analysis. Panel B of Table 1 describes

[8] Eckbo and Norli (2005) provide an excellent review of the literature associated with aggregate liquidity risk and expected returns.

Table 1
Descriptive statistics.

Panel A presents a description of each proxy variable for various calendar dates: January 1988, January 1993, January 1998, and December 2002. Proxies are estimated for all U.S.-domiciled common stocks listed on the NYSE and NASDAQ. For each calendar date, the *Idiosyncratic Risk* (*SIGMA*) is the standard deviation of the excess weekly returns (firm return minus CRSP value weighted return) computed over the prior 52 weeks (week ending defined as of Wednesday's close). The *I/B/E/S Analyst Forecast Dispersion* is the standard deviation of I/B/E/S earnings per share forecasts for the next fiscal year end, scaled by the forecast mean. The *Relative Short Interest* (*RSI*) is measured as the short interest divided by the number of outstanding shares. The *Institutional Ownership* (*IO*) is measured by dividing the reported number of shares held by institutions (SEC 13F filings obtained from Thomson Financial) by the total number of outstanding shares reported by CRSP. Panel B lists the total number of U.S. domiciled common stocks listed on CRSP, along with both the number and percentage without analyst coverage on I/B/E/S.

Panel A: Descriptive statistics for *SIGMA*, *RSI*, and *IO*

Dependent variable	Date	No. obs.	Mean	First percentile	First quartile	Median	Third quartile	99th percentile
Idiosyncratic risk: SIGMA	198 801	5179	0.0748	0.0277	0.0454	0.0637	0.0919	0.2175
	199 301	4930	0.0771	0.0182	0.0423	0.0639	0.0953	0.2719
	199 801	6414	0.0733	0.0221	0.0414	0.0628	0.0917	0.2317
	200 212	4794	0.0835	0.0249	0.0461	0.0689	0.1060	0.2648
Relative short interest (%): RSI	198 801	1145	0.0083	0.0000	0.0009	0.0026	0.0071	0.0981
	199 301	4166	0.0105	0.0000	0.0006	0.0023	0.0086	0.1236
	199 801	6111	0.0157	0.0000	0.0005	0.0038	0.0163	0.1605
	200 212	4413	0.0266	0.0000	0.0013	0.0096	0.0213	0.2333
Institutional ownership (%): IO	198 801	4701	0.2131	0.0008	0.0463	0.1527	0.3314	0.7323
	199 301	4962	0.2687	0.0010	0.0666	0.2114	0.4305	0.8195
	199 801	6551	0.3197	0.0009	0.1000	0.2658	0.5151	0.9006
	200 212	4686	0.4007	0.0009	0.1238	0.3676	0.6494	0.9934

Panel B: I/B/E/S analyst coverage of CRSP listed firms

	Date	Total no. CRSP firms	% Without analyst coverage
Analyst coverage on I/B/E/S	198 801	5923	51.12
	199 301	5607	43.25
	199 801	7132	31.35
	200 212	4971	36.07

the fraction of CRSP firms without analyst coverage. While the fraction has declined over the sample period, over 36% of firms had no I/B/E/S analyst coverage at the end of 2002.

2. Baseline cross-sectional tests

Table 2 presents baseline cross-sectional tests of the effects of volatility on expected returns, without regard to visibility or *RSI*, for the universe of all CRSP listed common

Table 2
Abnormal returns as a function of idiosyncratic risk.

Calendar time portfolio abnormal returns are shown as a function of idiosyncratic risk (*SIGMA*) for all CRSP listed common stocks (CRSP share codes 10 and 11) of U.S. domiciled NYSE and NASDAQ firms. *SIGMA* is the standard deviation of the excess weekly returns (firm return minus CRSP value weighted return) computed over the prior 52 weeks (week ending on Wednesday's close). *SIGMA* deciles are assigned annually at the end of June, beginning with June 1988 and ending with June 2002) by sorting all NYSE and NASDAQ firms on *SIGMA*. The abnormal returns are computed by forming equally weighted calendar-time portfolios of 12 month horizon and regressing the excess portfolio returns ($R_{p,t}-R_{f,t}$) on a four-factor model containing the three Fama and French (1993) risk factors (R_m-R_f, *SMB*, *HML*), as well as the momentum factor of Carhart (1997) (*UMD*). Calendar time portfolios are re-balanced once per year at the end of June. The estimation method is OLS. The abnormal return for each sub-sample is the intercept (α_p) from the following regression:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t}.$$

We also report the long-term abnormal return of a long-short (or zero-investment) portfolio, consisting of long positions of stocks in the highest *SIGMA* decile and short positions of stocks in the lowest *SIGMA* decile. The long-short portfolio abnormal returns are computed by forming calendar-time portfolios of 12-month horizon and regressing the difference in portfolio returns ($R_{sigma\,10,t}-R_{sigma\,1,t}$) on the four-factor model: The abnormal return for each sub-sample is the intercept or alpha (α_p) from the following regression:

$$R_{high-sigma,t} - R_{low-sigma,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + \varepsilon_{p,t}.$$

Monthly abnormal returns are expressed in decimal point notation. For example, an abnormal return of 0.00290 represents 29.0 bps per month. For each portfolio, the monthly mean number of firms is reported as "Mean No. obs." The *t*-statistics (one-tail test) reporting positive statistical significance are shown in brackets below the intercepts and are computed from the intertemporal variation in the monthly calendar-time portfolio returns. Results are for the July 1988 to June 2003 period.

	Idiosyncratic risk decile (*SIGMA*)											
	1st decile (lowest)	2nd decile	3rd decile	4th decile	5th decile	6th decile	7th decile	8th decile	9th decile	10th decile (highest)	Long-short portfolio: deciles 10−1	*t*-Statistic of long-short portfolio
Abnormal return	0.00290 [1.89]**	0.00223 [1.44]*	0.00155 [1.04]	0.00094 [0.67]	−0.00015 [−0.13]	−0.00058 [−0.57]	−0.00100 [−0.96]	0.00200 [1.46]*	0.00387 [1.65]**	0.00837 [1.96]**	0.00547	[0.98]
Mean no. obs.	537	533	530	524	526	523	518	515	503	461		

*, **, *** denotes positive statistical significance at the 10%, 5% and 1% levels, respectively.

stocks of U.S.-domiciled NYSE and NASDAQ firms. We present the monthly abnormal returns for portfolios formed at the end of each June and held for the next year as a function of idiosyncratic volatility (*SIGMA*).[9] *SIGMA* deciles are assigned to each stock by sorting all NYSE and NASDAQ firms on *SIGMA*. The abnormal returns are computed by forming equally weighted calendar-time portfolios with 12-month horizons and regressing the excess portfolio returns ($R_{p,t}$–$R_{f,t}$) on the four Fama–French–Carhart monthly factors. The abnormal return for each sub-sample is the intercept (α_p) from the regression.[10]

The last two columns in Table 2 shows the abnormal return of the long-short portfolio that takes long positions of stocks in the highest *SIGMA* decile, and short positions in stocks in the lowest *SIGMA* decile. The *t*-statistic of the long-short portfolio indicates the statistical significance of the difference of the measured mean return from zero.

There is no evidence in Table 2 of any consistent relationship between abnormal returns and *SIGMA*: the abnormal return point estimates across the 10 *SIGMA* deciles do not appear to follow any particular trend, and the long-short portfolio returns are not statistically significant. In short, as others have noted, there is no evidence here to provide *unconditional* support for Merton's hypothesis.

3. Idiosyncratic risk and return as a function of *IO*

Having established baseline (unconditional) results for the cross-sectional relationship between *SIGMA* and abnormal returns, we now focus our analysis on the space in which the assumptions underlying Merton's IRH are best satisfied. In particular, Merton (1987) predicts that idiosyncratic risk will be priced for lower-visibility firms, but not for high-visibility firms. We also hypothesize that Merton's IRH will be difficult to detect among more heavily shorted firms (which tend to have high *SIGMA* values) because heavily shorted firms are known to produce negative abnormal returns. Unfortunately, although we can state that Merton's hypothesis should be most easily observed where firms have low visibility (low *IO*) and low dispersion of opinion (low *RSI*), the IRH does not provide guidance as to how low either of these proxies should be in order for the underlying assumptions to be valid. That is an empirical question.

To address this empirical question, we present Table 3, Panel A. Considering the *IO* percentage as our visibility metric, at the end of June in each year, we sort all firms on the *IO* percentage and create four *IO* quartile groups. We next sort each *IO* grouping into quartiles based on *RSI*. Firms within each of these sixteen *IO*/*RSI* groupings are further sorted into deciles based on idiosyncratic risk (*SIGMA*). We are left with 160 *IO*–*RSI*–*SIGMA* sorted portfolios. The abnormal return reported for each portfolio is the intercept (α_p) from the four-factor OLS regression. We also report the associated *t*-statistic. To facilitate our analysis, we also construct long-short (zero-investment)

[9]Longer holding periods are preferable because Merton's (1987) hypothesis is about long-term steady-state returns. In contrast, Miller (1977) is about the near-term underperformance associated with the initial overpricing and the subsequent convergence to fundamentals. This dichotomy highlights the problem faced when conducting tests intended to disentangle Merton-effects from Miller-effects.

[10]These tests are conducted using OLS regressions, but results in this table and elsewhere are not sensitive to the use of the OLS approach. In an alternative specification, we weigh monthly excess returns by the square root of the number of firms in the portfolio each month, These WLS regressions produce very similar point estimates and significance values.

Table 3
Abnormal returns as a function of excess-return-based idiosyncratic risk, conditioned on *institutional ownership* and *relative short interest*.

For each end of June, beginning with 1988 and ending with 2002, all common stocks of U.S. domiciled NYSE and NASDAQ firms are first sorted on the *Institutional Ownership* percentage (*IO*) into quartiles. In Panel A, we next sort each *IO* quartile into quartiles based on the *Relative Short Interest* (*RSI*), and then further sort each of these sixteen *IO*/*RSI* groups into deciles based on the idiosyncratic risk (*SIGMA*). *SIGMA* is the standard deviation of the excess weekly returns (firm return minus CRSP value-weighted return) computed over the prior 52 weeks (week ending defined as of Wednesday's close).

In Panel B, the three lowest *IO* quartiles (1, 2, and 3) are grouped together, while quartile 4 (highest) remains a separate group. We next sort each *IO* grouping into halves based on *Relative Short Interest* (*RSI*). Next, firms within each of these four *IO*/*RSI* groupings are further sorted into deciles based on idiosyncratic risk (*SIGMA*). We also perform a sorting (unconditional of *RSI*) of these two *IO* groupings into *SIGMA* deciles. In both Panels A and B, we report the long-term abnormal returns for each portfolio. These are computed by forming equally weighted calendar-time portfolios of 12-month horizon and regressing the excess portfolio returns ($R_{p,t}-R_{f,t}$) on the three Fama and French (1993) risk factors (R_m-R_f, SMB, HML) as well as Carhart's (1997) momentum factor (UMD). The abnormal return for each portfolio is the intercept (α_p) from the following regression:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t}.$$

We also report the long-term abnormal return of long-short (or zero-investment) calendar-time portfolios, consisting of a long position in stocks with the highest *SIGMA* decile and a short position in stocks from the lowest *SIGMA* decile. The long-short portfolio abnormal returns are computed by forming calendar-time portfolios of 12-month horizon and regressing the difference in portfolio returns ($R_{sigma\,10,t}-R_{sigma\,1,t}$) on the same four factors. The abnormal return is the intercept or alpha (α_p) from the following regression:

$$R_{sigma\,10,t} - R_{sigma\,1,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t}.$$

Calendar-time portfolios are re-balanced once per year at the end of June. The estimation method is OLS. Monthly abnormal returns expressed in decimal point notation. For example, an abnormal return of 0.00467 corresponds to 46.7 bps per month. The *t*-statistics (one-tail test) reporting positive statistical significance are shown in the last column and are computed from the intertemporal variation in the monthly calendar-time portfolio returns. Results are for the July 1988 to June 2003 period.

Table 3 (*continued*)

Panel A: Firms sorted into *institutional ownership* (*IO*) quartiles; with each *IO* quartile sorted into *relative short interest* (*RSI*) halves; and each *IO*/*RSI* group further sorted into *idiosyncratic risk* (*SIGMA*) deciles

Institutional ownership (*IO*) quartile	*Relative short interest* (*RSI*) group	*Idiosyncratic risk decile* (*SIGMA*) 1st decile (lowest)	2nd decile	3rd decile	4th decile	5th decile	6th decile	7th decile	8th decile	9th decile	10th decile (highest)	Long-short portfolio [decile 10]–[decile 1] abnormal returns	Long-short portfolio *t*-statistic
1 (lowest quartile)	RSI1	0.00467	0.00750	0.00104	0.00832	0.00114	0.00728	0.01480	0.01109	0.01385	0.00828	0.00361	[0.48]
	RSI2	0.00520	0.00314	0.00691	0.00317	0.00072	0.00591	0.00321	0.00106	0.01542	0.00883	0.00363	[0.41]
	RSI3	0.00392	0.00129	−0.00142	−0.00397	−0.00123	−0.00255	0.00127	0.00691	0.00213	0.00750	0.00358	[0.40]
	RSI4	0.00108	−0.00367	−0.00205	−0.00313	−0.00837	−0.01281	−0.00151	−0.00840	0.00178	−0.00810	−0.00919	[−0.93]
2	RSI1	0.00421	0.00591	0.00693	0.00184	0.00585	0.00138	0.00279	0.01220	0.00782	0.01322	0.00901	[1.34]*
	RSI2	0.00754	0.00651	0.00443	0.00445	0.00090	0.00110	0.00320	0.00749	0.00910	0.01693	0.00940	[1.28]*
	RSI3	0.00322	0.00416	0.00362	−0.00130	0.00213	0.00353	0.00108	0.00605	0.01451	0.01574	0.01252	[1.64]*
	RSI4	−0.00181	−0.00446	−0.00635	−0.00410	−0.00446	−0.00319	−0.00426	−0.00360	0.00040	−0.00663	−0.00482	[−0.65]
3	RSI1	0.00403	0.00283	0.00094	−0.00045	0.00382	−0.00132	−0.00141	−0.00290	0.00380	0.00983	0.00580	[1.26]
	RSI2	0.00271	0.00145	0.00207	0.00199	0.00116	0.00458	0.00273	0.00416	0.00405	0.00951	0.00680	[1.47]*
	RSI3	0.00071	0.00198	−0.00034	0.00312	−0.00053	−0.00420	0.00140	−0.00256	0.00505	0.00202	0.00130	[0.27]
	RSI4	−0.00026	0.00167	−0.00197	0.00253	0.00004	−0.00723	−0.00562	−0.00414	−0.00087	−0.00211	−0.00185	[−0.32]
4 (highest quartile)	RSI1	0.00191	0.00190	0.00088	−0.00019	0.00294	0.00019	0.00325	−0.00186	−0.00002	0.00104	−0.00086	[−0.24]
	RSI2	0.00273	0.00099	0.00051	0.00117	0.00045	0.00061	0.00059	−0.00110	−0.00013	0.00168	−0.00105	[−0.30]
	RSI3	0.00096	0.00148	0.00241	0.00115	0.00010	0.00054	0.00326	−0.00120	−0.00164	0.00441	0.00345	[0.83]
	RSI4	−0.00029	−0.00181	−0.00290	−0.00362	0.00074	−0.00117	0.00058	0.00348	0.00376	−0.00424	−0.00395	[−0.82]

Panel B: *Institutional ownership* (*IO*) quartiles 1–3 grouped together, quartile 4 (highest) kept separate; with each *IO* grouping also further sorted into *relative short interest* (*RSI*) halves

1, 2 and 3 (lowest three quartiles)	All *RSI*	0.00346	0.00277	0.00268	0.00016	−0.00119	−0.00127	0.00179	0.00288	0.00456	0.00764	0.00418	[0.73]
	Lower *RSI* half	0.00509	0.00512	0.00355	0.00291	0.00107	0.00005	0.00675	0.00616	0.00919	0.01482	0.00973	[1.66]**
	Upper *RSI* half	0.00132	0.00037	0.00125	−0.00287	−0.00179	−0.00310	−0.00228	−0.00035	0.00091	−0.00130	−0.00262	[−0.42]
4 (highest)	All *RSI*	0.00191	0.00115	0.00042	0.00014	0.00017	−0.00029	0.00109	−0.00080	0.00077	0.00137	−0.00054	[−0.18]
	Lower *RSI* half	0.00201	0.00159	0.00081	0.00118	0.00025	0.00147	0.00171	−0.00023	−0.00173	0.00194	−0.00007	[−0.02]
	Upper *RSI* half	0.00081	0.00107	−0.00065	−0.00108	−0.00140	0.00152	−0.00003	0.00130	0.00187	−0.00032	−0.00114	[−0.28]

*, **, *** denotes positive statistical significance at the 10% 5% and 1% levels, respectively.

portfolios for each *IO–RSI* combination. Using the method presented in Table 2 discussion, these portfolios consist of a long position in stocks from the highest *SIGMA* decile and a short position in stocks from the lowest *SIGMA* decile. These long-short portfolios are presented in the two right-most columns of Table 3.

To facilitate the following discussion, we define all the portfolios in terms of the *IO* quartile and the *RSI* quartile so that ($IO = 1$, $RSI = 1$) refers to the set of firms in the smallest *IO* quartile and the smallest *RSI* quartile. Likewise, ($IO = 4$, $RSI = 4$) refers to the set of firms in the largest *IO* quartile and the largest *RSI* quartile. The space over which Merton's assumptions are best met clearly must include the firms in ($IO = 1$, $RSI = 1$). Likewise, it seems obvious that we must exclude from consideration all those portfolios in the space ($IO = 4$, $RSI = 1,2,3,4$) and all those portfolios in the space($IO = 1,2,3,4$, $RSI = 4$). Among the remaining portfolios, we observe that ($IO = 3$, $RSI = 3$) has the lowest alpha value. This seems reasonable in that while neither *IO* nor *RSI* is in the highest quartile, both *IO* and *RSI* are above median for this set of firms. The next lowest alpha among the remaining long-short portfolios is ($IO = 1$, $RSI = 3$). Thus, $RSI < 3$ appears to be a useful point of bifurcation. Otherwise, *IO* quartiles 1, 2, and 3 each produce positive long-short portfolio alphas.

We note that none of the long-short alphas carry *t*-statistics that are significant at the 5% level. However, notice that all $SIGMA = 10$ portfolios and all long-short portfolio values are positive after excluding firms in *IO* quartile 4 and *RSI* quartile 4. In other words, *SIGMA* appears to be priced in accordance with Merton's (1987) hypothesis for low visibility firms, conditioned on low *RSI*. Because these portfolios are constructed using three variable sorts, the number of firms in each portfolio is relatively small, rendering the power of the test low. Thus, our effort to find suitable division points in the data must balance: (1) the need for defining *IO* and *RSI* narrowly enough to satisfy the assumptions of Merton's IRH against (2) the need for adequate portfolio size to ensure sufficient power of the tests.[11]

Panel B of Table 3 presents tests for the lowest three *IO* quartiles. By combining the three quartiles, we simplify the following exposition, highlight the economic significance of Merton's (1987) IRH by showing that it applies to a large fraction of traded U.S. stocks, and increase the power of the tests. The first line of Panel B presents the results for these lower-visibility firms without conditioning on *RSI*. This line is labeled "All *RSI*". These tests are an unconditional test of Merton's IRH on lower-visibility firms without consideration of short interest levels. Subdividing the lower-*IO* firms into *SIGMA* deciles, we obtain the four-factor abnormal return results for each *SIGMA*-grouped portfolio.

The results in the "All *RSI*" line are very similar to the baseline results in Table 2. There is limited evidence of a relation between abnormal returns and *SIGMA* deciles 10 and 9 have higher alpha point estimates than any of the other *SIGMA*-based portfolios. Otherwise, the point estimates of abnormal returns across the 10 *SIGMA* deciles do not

[11] This cut of the data excludes the data from ($IO = 2$, RSI = 3), which also reports a relatively high long-short portfolio alpha. An alternative cut of the data might define the Merton space to exclude portfolios in the highest quartile of either *IO* or the highest quartile of RSI, and also exclude the quartile ($IO = 3$, RSI = 3), where both proxy variables are relatively high. This definition of the Merton space would extend as far as ($IO = 2$, RSI = 3) and ($IO = 3$, RSI = 2). This division produces results that are very similar to that described in the body of the paper. In fact, a point estimate of the $SIGMA = 10$ portfolio is over 16% annually. However, the *t*-statistic on the long-short portfolio is significant at only the 10% level. In any event, Panel A provides a great degree of detail for the reader to consider alternative bifurcations of the data.

follow a discernable trend. The long-short portfolio return point estimate is positive, but it is not statistically significant.

3.1. Conditioning on short interest

The second and third lines of Panel B of Table 3 subdivide the lower-*IO* firms between those with low *RSI* and those with higher *RSI*, based upon the median *RSI* level of firms in the low-*IO* group. We have hypothesized that evidence of Merton's IRH may be difficult to detect among more heavily shorted firms because such firms are known to produce negative abnormal returns, and *RSI* is positively correlated with *SIGMA*. Line 2 of Panel B, labeled "Lower *RSI* half" is composed of low-*IO* firms with relatively little shorting activity. We expect to find evidence that *SIGMA* is priced in this subset of firms, and we do. Among these low-*RSI* firms, firms in the 10th-decile *SIGMA* portfolio earn monthly abnormal returns of 1.482% per month. This is equivalent to a compounded annual return greater than 19.3%. The 9th-decile portfolio earns the second-highest alpha among all the *SIGMA*-based portfolios, and portfolios 7 and 8 return the third- and fourth-highest alpha values. However, the pattern of abnormal returns across all deciles is not strictly monotonic. Returns decrease slightly from decile 1 through decile 6, but abnormal returns rise sharply as *SIGMA* increases further. Despite this lack of strict monotonicity, the long-short portfolio constructed by shorting first-decile stocks and purchasing 10th-decile firms earns an economically and statistically significant return of 0.973% monthly (12.3% annually). The long-short portfolio alpha is significant at the 5% level.

The third line of Panel B of Table 3 presents portfolios for the more heavily shorted lower-*IO* firms. These firms satisfy Merton's low visibility assumption, but the confounding effects of relatively high shorting are present. No pattern is apparent in the *SIGMA*-based portfolios, and the long-short portfolio return is actually negative, rather than positive as the hypothesis would predict. Thus, no evidence here supports Merton's hypothesis. That idiosyncratic risk is not priced for low-*IO*, high-*RSI* firms is consistent with the findings of Asquith et al. (2005), who identify these firms as most likely to be overvalued in a Miller sense.

The last three lines of Panel B of Table 3 replicate the first three lines of the table, except that the analysis focuses on the highest-quartile *IO* firms, rather than the lower-*IO* firms. Merton's (1987) hypothesis suggests that *SIGMA* should not be priced for these firms because they have high visibility. Consistent with this conjecture, none of the long-short portfolios for high-*IO* firms produce economically or statistically significant alphas. *SIGMA* appears to be priced only among low-visibility firms with low short interest.

3.2. Robustness tests

We conduct two types of robustness tests. First, we repeat the analysis in Table 3 using *SIGMA* computed as the standard deviation of residuals from the four-factor Fama–French–Carhart model rather than the standard deviation of excess returns. The results are presented in Table 4 and are almost identical to those reported in Table 3. The relation between *SIGMA* and returns continues to be positive for stocks in the Merton region of low *IO* and low *RSI*.

For our second robustness test, we repeat the analysis in Tables 3 using alternative model specifications. The results are presented in Table 5. Panel A of Table 5 presents the results obtained with four alternative asset pricing models: the CAPM, the Fama–French three-factor model, the Fama–French–Carhart four-factor model augmented with the Eckbo–Norli liquidity factor, and a simple risk-free-rate adjusted model. The first column in Panel A restates the long-short portfolio results shown in the last two columns of Table 3, Panel B, for easy reference. The other columns in Panel A show the abnormal returns of the same portfolios under alternative pricing models.

For low-*IO* firms unconditional on *RSI*, only the liquidity augmented five-factor model produces statistically significant positive alphas for the long-short portfolios. However, after conditioning on *RSI*, the alpha is significantly positive only for firms with low levels of short interest, suggesting that the unconditional result actually is driven by this subset. In general, for stocks with low *IO* and low *RSI*, the effect of *SIGMA* on stock returns is significantly positive across the asset pricing models, except for the CAPM where the effect remains positive but does not attain statistical significance. We note that the five-factor model produces the strongest results in a statistical sense, but the raw return model produces the largest alpha point estimates: after accounting for size, book-to-market, momentum, liquidity and the market returns, firms in the highest *SIGMA* decile earn approximately 1.387% per month (17.9% per year) *more* than firms in the lowest *SIGMA* decile.

Among firms with low *IO* but high *RSI*, long-short abnormal returns are generally negative. Firms in the highest *IO* quartile also produce no positive and statistically significant long-short intercepts, irrespective of *RSI* conditioning. The results of Panel A of Table 5 provide clear additional evidence consistent with Merton's IRH.

Panel B of Table 5 considers alternative portfolio weighting methods, alternative rebalancing frequencies, and alternative investment horizons for the standard four-factor asset-pricing model. Again, for easy reference, the leftmost column of Panel B repeats the results from the leftmost column of Panel A. These portfolios are equally weighted, rebalanced at the end of June each year, and held for a one-year horizon. The next column present results when portfolios are rebalanced every month, and selected stocks are held in the portfolio for a full year. This method necessitates overlapping portfolio formation periods. Portfolios are formed every month, but because the stocks are held for the ensuing 12 months, 1/12 of the portfolio changes every month. Stocks that remain low-visibility and lightly shorted for several months will end up included in the portfolio multiple times. However, this method will not bias the result in any particular direction. Moreover, any resulting cross-correlation is automatically accounted for in the calendar time portfolio methodology, because the standard errors are computed from intertemporal (rather than cross-sectional) variation in returns.

Results obtained with monthly rebalancing are consistent with those obtained with annually rebalancing. The point estimate of the long-short alpha for the low-*IO*, low-*RSI* firms is economically significant at 0.95% per month (11.4% per year). In untabulated results, we also find that more aggressive parsing of the data produces long-short intercepts of greater magnitudes. For example, when the analysis is focused narrowly on firms at the intersection of the lowest *IO* and lowest *RSI* quartiles (rather than the lower three-quarters of *IO* and the lower half of *RSI* firms), the 10th-decile *SIGMA* firms earn a highly significant 1.84% monthly abnormal return (24.5% annually).

The third set of results in Panel B of Table 5 corresponds to equally weighted portfolios with monthly rebalancing and monthly holding periods. For the one-month horizon portfolios, the alpha point estimate is positive (0.66% monthly), but the abnormal return

Table 4
Abnormal returns as a function of four-factor-based idiosyncratic risk, conditioned on *institutional ownership* and *relative short interest*.

For each end of June, beginning with 1988 and ending with 2002, all common stocks of U.S. domiciled NYSE and NASDAQ firms are first sorted on the *institutional ownership* (*IO*) percentage into quartiles. In Panel A, we next sort each *IO* quartile into quartiles based on the *relative short interest* (*RSI*), and then further sort each of these sixteen *IO*/*RSI* groups into deciles based on the idiosyncratic risk (*SIGMA*). *SIGMA* is the standard deviation of the error term from the Fama/French and Carhart four-factor model computed over the prior 52 weeks of stock returns (week ending on Wednesday's close).

In Panel B, the three lowest *IO* quartiles (1, 2, and 3) are grouped together, while quartile 4 (highest) remains a separate group. We next sort each *IO* grouping into halves based on *relative short interest* (*RSI*). Next, firms within each of these four *IO*/*RSI* groupings are further sorted into deciles based on idiosyncratic risk (*SIGMA*). We also perform a sorting (unconditional of *RSI*) of these two *IO* groupings into *SIGMA* deciles. In both Panels A and B, we report the long-term abnormal returns for each portfolio. These are computed by forming equally weighted calendar-time portfolios of 12-month horizon and regressing the excess portfolio returns ($R_{p,t}-R_{f,t}$) on the three Fama and French (1993) risk factors (R_m-R_f, SMB, HML), as well as Carhart's (1997) momentum factor (UMD). The abnormal return for each portfolio is the intercept (α_p) from the following regression:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t}.$$

We also report the long-term abnormal return of long-short (or zero-investment) calendar-time portfolios, consisting of a long position in stocks with the highest *SIGMA* decile and a short position in stocks from the lowest *SIGMA* decile. The long-short portfolio abnormal returns are computed by forming calendar-time portfolios of 12-month horizon and regressing the difference in portfolio returns ($R_{\text{sigma }10,t}-R_{\text{sigma }1,t}$) on the same four factors. The abnormal return is the intercept or alpha (α_p) from the following regression:

$$R_{sigma\ 10,t} - R_{sigma\ 1,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t}.$$

Calendar-time portfolios are re-balanced once per year at the end of June. The estimation method is OLS. Monthly abnormal returns expressed in decimal point notation. For example, an abnormal return of 0.00456 corresponds to 45.6 bps per month. The *t*-statistics (one-tail test) reporting positive statistical significance are shown in the last column and are computed from the intertemporal variation in the monthly calendar-time portfolio returns. Results are for the July 1988 to June 2003 period.

Panel A: Firms sorted into *institutional ownership* (*IO*) quartiles; with each *IO* quartile sorted into *relative short interest* (*RSI*) halves; and each *IO*/*RSI* group further sorted into *idiosyncratic risk* (*SIGMA*) deciles

Institutional ownership (IO) quartile	Relative short interest (RSI) group	Idiosyncratic risk decile (SIGMA)										Long-short portfolio [decile 10]−[decile 1] abnormal returns	Long-short portfolio *t*-statistic
		1st decile (lowest)	2nd decile	3rd decile	4th decile	5th decile	6th decile	7th decile	8th decile	9th decile	10th decile (highest)		
1 (lowest quartile)	RSI1	0.00456	0.00709	0.00127	0.00828	0.00316	0.00734	0.01469	0.00886	0.01455	0.00800	0.00344	[0.46]
	RSI2	0.00547	0.00251	0.00822	0.00318	0.00205	0.00120	0.00042	0.00317	0.01907	0.00719	0.00172	[0.20]
	RSI3	0.00370	0.00204	−0.00116	−0.00333	−0.00237	−0.00246	−0.00130	0.01001	0.00220	0.00637	0.00268	[0.29]
	RSI4	0.00069	−0.00260	−0.00299	−0.00188	−0.01207	−0.00835	−0.00483	−0.00519	−0.00066	−0.00783	−0.00851	[−0.87]
2	RSI1	0.00414	0.00607	0.00556	0.00275	0.00813	−0.00124	0.00386	0.01060	0.00866	0.01398	0.00984	[1.51]*
	RSI2	0.00784	0.00602	0.00524	0.00262	0.00309	0.00036	0.00265	0.00760	0.00892	0.01740	0.00956	[1.28]*
	RSI3	0.00351	0.00482	0.00208	−0.00231	0.00482	0.00252	0.00287	0.00617	0.01152	0.01655	0.01305	[1.72]**
	RSI4	−0.00147	−0.00520	−0.00674	−0.00280	−0.00116	−0.00534	−0.00524	−0.00371	−0.00179	−0.00567	−0.00420	[−0.57]
3	RSI1	0.00364	0.00262	0.00229	0.00096	0.00091	−0.00011	−0.00339	−0.00179	0.00399	0.01060	0.00696	[1.44]*
	RSI2	0.00298	0.00172	0.00145	0.00175	0.00136	0.00404	0.00327	0.00290	0.00420	0.01075	0.00778	[1.59]*
	RSI3	0.00123	0.00023	0.00027	0.00233	0.00157	−0.00088	−0.00065	−0.00183	0.00306	0.00129	0.00006	[0.01]
	RSI4	−0.00005	0.00214	−0.00046	0.00277	−0.00291	−0.00746	−0.00634	−0.00077	−0.00451	−0.00054	−0.00050	[−0.09]
4 (highest quartile)	RSI1	0.00262	0.00056	0.00030	0.00054	0.00267	0.00224	0.00059	0.00025	−0.00122	0.00157	−0.00105	[−0.30]
	RSI2	0.00277	0.00096	0.00033	0.00089	0.00121	−0.00030	0.00016	0.00135	−0.00133	0.00151	−0.00126	[−0.35]
	RSI3	0.00069	0.00221	0.00131	0.00035	0.00029	0.00314	0.00079	−0.00021	0.00016	0.00283	0.00214	[0.55]
	RSI4	−0.00054	−0.00189	−0.00309	−0.00424	−0.00052	0.00019	0.00280	0.00231	0.00398	−0.00453	−0.00398	[−0.89]

Panel B: *Institutional ownership* (*IO*) quartiles 1–3 grouped together, quartile 4 (highest) kept separate; with each *IO* grouping also further sorted into *relative short interest* (*RSI*) halves

1, 2 and 3 (lowest three quartiles)	All *RSI*	0.00351	0.00306	0.00154	0.00097	0.00066	−0.00143	0.00166	0.00243	0.00570	0.00668	0.00316	[0.56]
	Lower *RSI* half	0.00574	0.00460	0.00329	0.00230	0.00240	−0.00055	0.00718	0.00652	0.00850	0.01460	0.00886	[1.55]*
	Upper *RSI* half	0.00124	0.00041	0.00083	−0.00216	−0.00227	−0.00298	−0.00127	−0.00099	0.00045	−0.00124	−0.00248	[−0.40]
4 (highest)	All *RSI*	0.00193	0.00051	0.00036	0.00011	0.00001	0.00043	0.00063	0.00003	0.00049	0.00146	−0.00047	[−0.16]
	Lower *RSI* half	0.00248	0.00083	0.00028	0.00040	0.00140	0.00145	0.00203	−0.00156	−0.00069	0.00227	−0.00022	[−0.08]
	Upper *RSI* half	0.00074	0.00106	−0.00084	−0.00159	0.00018	0.00037	0.00061	0.00230	0.00069	−0.00021	−0.00095	[−0.26]

*, **, *** denotes positive statistical significance at the 10% 5% and 1% levels, respectively.

Table 5

Robustness tests of long-short portfolios conditioned on *institutional ownership*.

This table presents robustness tests of the long-short portfolio regressions presented in Table 3. Only long-short portfolio results are reported below. In Panel A, we examine robustness across various alternative calendar time pricing models, while maintaining the equally weighted portfolio, annual portfolio holding periods, and annual portfolio rebalancing procedure of Table 3. In Panel B, we only present the four-factor model, while varying the portfolio holding periods and frequency of portfolio rebalancing, and we also present results where the firms are weighted by the logarithm of market capitalization.

We report the long-term abnormal return of long-short (or zero-investment) calendar time portfolios, consisting of a long position in stocks with the highest *SIGMA* decile and a short position in stocks with the lowest *SIGMA* decile. *Idiosyncratic Risk* (*SIGMA*) is the standard deviation of the excess weekly returns (firm return minus CRSP value-weighted return) computed over the prior 52 weeks (week ending defined as of Wednesday's close). The long-short portfolio abnormal returns are computed by forming calendar-time portfolios of either 12-month horizon (both in Panels A and B) or one-month horizon (Panel B only), and regressing the difference in portfolio returns ($R_{sigma\,10,t} - R_{sigma\,1,t}$) on four-factor, five-factor, Fama/French three-factor, CAPM, and Raw return models: The five-factor model augments the four-factor model with the *LMH* liquidity risk factor, factor of Eckbo and Norli (2005), where *LMH* is the monthly difference in returns between low and high liquidity firms. In Panel A we utilize equally weighted portfolios, while in Panel B we utilize both equally and log-of-market-capitalization-weighted portfolios. The abnormal return for each sub-sample is the intercept, t (α_p) from the following regression (five-factor model shown):

$$R_{sigma\,10,t} - R_{sigma\,1,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t}.$$

For Panel A, we repeat the Table 3 process where calendar-time portfolios are re-balanced once per year at the end of June, and the results are for the July 1988 to June 2003 period. In Panel B, we explore: (1) one-month holding periods with monthly rebalancing and (2) 12-month holding periods with monthly rebalancing, where results of (1) and (2) are presented for the February 1988 to December 2002 periods. The estimation method is OLS. An abnormal return of 0.00418 below is to be interpreted as an abnormal return of 41.8 bps per calendar month. The *t*-statistics (one-tail test) reporting positive statistical significance are shown in brackets beside the intercepts and are computed from the intertemporal variation in the monthly calendar-time portfolio returns. For expositional convenience, the first columns of both Panels A and B (four-factor results) restate long-short-portfolio results from Table 3.

Panel A: Alternative asset pricing models

Institutional ownership (*IO*) quartile	*Relative short interest* (*RSI*) group	Asset pricing model									
		4-factor		5-factor		3-factor		CAPM		Raw returns	
		Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic
1, 2 and 3 (lowest three quartiles)	All *RSI* values	0.00418	[0.73]	0.00936	[1.70]**	−0.00101	[−0.18]	−0.00520	[−0.91]	0.00812	[0.88]
	Lower *RSI* half	0.00973	[1.66]**	0.01387	[2.46]***	0.00805	[1.58]	0.00515	[0.97]	0.01652	[1.99]**
	Upper *RSI* half	−0.00262	[−0.42]	0.00302	[0.51]	−0.01037	[−1.70]	−0.01568	[−2.42]	−0.00092	[−0.09]

Table 5 (*continued*)

4 (highest)	All *RSI* values	−0.00054	[−0.18]	0.00311	[1.10]	−0.00540	[−1.75]	−0.01122	[−2.78]	−0.00118	[−0.17]
	Lower *RSI* half	−0.00007	[−0.02]	0.00218	[0.78]	−0.00348	[−1.25]	−0.00774	[−2.25]	0.00018	[0.03]
	Upper *RSI* half	−0.00114	[−0.28]	0.00306	[0.81]	−0.00548	[−1.40]	−0.01241	[−2.49]	−0.00159	[v0.21]

Panel B: Alternative rebalancing periods, investment horizons, and portfolio weighting

Institutional ownership (*IO*) quartile	*Relative short interest* (*RSI*) group	Portfolio weighting method											
		Equally weighted						Log-value-weighted					
		Rebalancing frequency											
		Annual		Monthly		Monthly		Annual		Monthly		Monthly	
		Investment horizon											
		One year		One year		One month		One year		One year		One month	
		Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic
1, 2 and 3(lowest three quartiles)	All RSI values	0.00418	[0.73]	0.00300	[0.51]	−0.00175	[−0.29]	0.01197	[1.91]**	0.01048	[1.63]*	0.00514	[0.78]
	Lower RSI half	0.00973	[1.66]**	0.00905	[1.55]*	0.00662	[1.12]	0.01683	[2.64]***	0.01612	[2.51]***	0.01289	[1.96]**
	Upper RSI half	−0.00262	[−0.42]	−0.00364	[−0.58]	−0.01090	[−1.60]	0.00617	[0.93]	0.00476	[0.71]	−0.00295	[−0.41]
4 (highest)	All RSI values	−0.00054	[−0.18]	0.00069	[0.24]	−0.00143	[−0.43]	0.00106	[0.35]	0.00198	[0.68]	−0.00022	[−0.07]
	Lower RSI half	−0.00007	[−0.02]	0.00226	[0.86]	0.00321	[1.00]	0.00163	[0.56]	0.00381	[1.44]*	0.00570	[1.75]**
	Upper RSI half	−0.00114	[−0.28]	−0.00037	[−0.11]	−0.00335	[−0.81]	−0.00022	[−0.06]	0.00077	[0.23]	−0.00223	[−0.55]

*, **, *** denotes positive statistical significance at the 10% 5% and 1% levels, respectively.

does not attain statistical significance at traditional levels. Although this result is short of traditional significance levels, one should consider the possibility that monthly holding periods may not be optimal for this analysis. Merton's (1987) hypothesis predicts positive steady-state returns as compensation for bearing risk. It does not predict a mispricing phenomenon (as Miller's (1977) theory does) that might be expected to correct over a shorter horizon. As long as firms retain limited visibility, the effect of *SIGMA* on expected returns should be detected over longer horizons (such as one year).

The right-hand side of Panel B of Table 5 presents results for value-weighted (as opposed to equally weighted) portfolios. Consistent with Ikenberry and Ramnath (2002), we use the natural logarithm of the market capitalization as the weight variable, instead of using the market capitalization directly. Ikenberry and Ramnath explain that "… given the extreme skewness observed in market equity values, strict cap-weighting can lead to perverse investment weights in some months. This assumption not only reflects an unrealistic investment policy, it can lead to less precise point estimates because of the noise in these less diversified portfolios" (Loughran and Ritter, 2000, p. 519). We follow Ikenberry and Ramnath and use log-value weighting to obtain much of the benefit of value weighting, while mitigating problems driven by extreme skewness in market values. Each of the three log-value weighted robustness tests produces results that remain consistent with prior findings.[12]

In untabulated tests, we repeat the analysis in Table 5 with idiosyncratic risk measured as the standard deviation of the residuals from the four-factor Fama/French–Carhart model, rather than weekly excess raw returns (firm return minus CRSP VWRETD index). The results are almost identical to those shown in Table 5.

Taken as a whole, the results in Tables 3–5 are broadly consistent with Merton's IRH. Idiosyncratic risk is priced for low-visibility firms when short selling is not prevalent. This result is economically important. We find evidence that idiosyncratic risk is priced for the least-shorted half of the stocks of the lowest three *IO* quartiles, i.e., about 38% of U.S. stocks.

4. Idiosyncratic risk and return for firms without analyst coverage

Another reasonable proxy for firm visibility is the level of analyst coverage. More than half the firms in our sample had no sell-side analyst coverage reported by IBES at the beginning of 1988. Even at the beginning of 2003, this fraction remained relatively high, at 36%. A lack of sell-side analyst scrutiny certainly seems consistent with low visibility in an IRH sense. Accordingly, we repeat our Merton (1987) tests on firms lacking analyst coverage by mirroring the tests previously performed on low-*IO* firms. Table 6 reports these results for our standard method; annual rebalancing, one year investment horizon, and four-factor asset-pricing model.

The first row in Table 6 shows the cross-section of monthly abnormal returns for all zero-analyst firms. Although these firms are not presorted on *RSI*, there is some evidence of a positive relation between *SIGMA* and abnormal returns. Specifically, the abnormal

[12] For completeness, we also examine results based on "strict" value weighting (i.e., without taking the natural log of the market capitalization). The results (not tabulated) do not attain statistical significance, consistent with Ikenberry and Ramnath's (2002) conjecture.

returns are monotonically increasing for *SIGMA* deciles 4–10. However, the long-short portfolio *t*-statistic does not denote statistical significance.

Once we control for *RSI*, we find results consistent with the IRH that are both economically and statistically significant. The second and third rows of Panel A in Table 6 report results for zero-analyst firms that have been further segregated into portfolios of low-*RSI* and high-*RSI* firms each month. Again, we segment these firms into deciles based on *SIGMA* ranking. Thus, the twenty portfolios presented in the second and third row of Panel A have an equal number of firms in each month of the analysis.

For zero-analyst firms that also have low *RSI*, the results strongly support Merton's hypothesis. Abnormal returns rise in a near-monotonic manner from the third *SIGMA* decile to the 10th decile. The 10th decile's abnormal return is 1.462% per month, which compounds to 19.0% annually. This is significantly higher than the abnormal return of the first decile (0.461% per month or 5.6% per year). The long-short portfolio abnormal return is also positive and statistically significant. In contrast, for zero-analyst firms with high *RSI* (relative to other zero-analyst firms); long-short portfolio returns are actually negative.

Table 7 presents robustness measures for the long-short portfolio alphas in Table 6. As we will show, the results observed in Table 6 prove to be quite robust to methodological variations. Table 7 follows the same format as Table 5. In Panel A, the zero-analyst, low-*RSI* firms produce statistically significant positive long-short abnormal returns for all pricing models considered. In contrast, high-*RSI* firms do not exhibit significantly positive abnormal long-short returns; in fact, some of the intercepts are negative. Moreover, although these zero-analyst firms are likely to be lightly traded, the results do not appear to be liquidity driven. The addition of a liquidity factor does not change the main conclusion from Table 6.

In Panel B of Table 7, we use the four-factor asset-pricing model and explore alternative portfolio weighting methods, rebalancing frequencies, and investment horizons. The first two columns of Panel B duplicate the long-short results from Table 6. For low-*RSI* firms, each alternative specification presented in Panel B produces an even more positive intercept of greater statistical significance, when compared to the leftmost equally weighted, annually rebalanced, 12-month portfolios. For example, when portfolios are rebalanced monthly and held for a one-year investment horizon, the log-value weighted long-short returns approach 1.8% per month (23.8% annually).[13] By contrast, none of the portfolios of more heavily shorted firms produce statistically significant positive alphas. In fact, the alphas are often negative.

For robustness, we repeat the analysis in Tables 5 and 6 with idiosyncratic risk (*SIGMA*) computed as the standard deviation of residuals from the Fama–French–Carhart four-factor model. The results (untabulated) are almost identical, and continue to provide very strong support for Merton's IRH.

5. Cross-sectional analysis (Fama–Macbeth regressions)

In Sections 3 and 4, we see the positive effect of *SIGMA* on expected returns for low visibility stocks, i.e., stocks that are in the lower half of the sample based on the *RSI* level. However, these results are based on portfolio selection methods that, of necessity, are somewhat arbitrary. To overcome this concern, we conduct a set of cross-sectional

[13]For robustness, we also measure idiosyncratic risk using the residuals from the four-factor Fama/French–Carhart model, with similar results throughout.

Table 6
Abnormal returns as a function of idiosyncratic risk, conditioned on *relative short interest* and absence of analyst coverage.

This table considers only common stocks with no I/B/E/S analyst coverage. These stocks are sorted into deciles based on *SIGMA*, and abnormal returns based on *SIGMA*-decile groups are presented as the first row of the table. *Idiosyncratic risk* (*SIGMA*) is the standard deviation of the excess weekly returns (firm return minus CRSP value-weighted return) computed over the prior 52 weeks (week ending defined as of Wednesday's close). We also sort stocks into halves based on *relative short interest* (*RSI*). Next, firms within each *RSI* grouping are further sorted into deciles based on *SIGMA*, producing a final sorting into 20 (2×10) portfolios. The portfolio assignments are conducted annually at the end of June (from 1988 to 2002). Abnormal returns for these portfolios are presented in the second and third rows. Abnormal returns are computed by forming equally weighted calendar-time portfolios of 12-month horizon and regressing the excess portfolio returns ($R_{p,t}$–$R_{f,t}$) on the three Fama and French (1993) factors (R_m–R_f, *SMB*, *HML*), as well as Carhart's (1997) momentum factor (*UMD*). The abnormal return for each portfolio is the intercept or alpha (α_p) from the following regression:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t}.$$

We also report the long-term abnormal return of long-short (or zero-investment) calendar-time portfolios, consisting of long positions in stocks with the highest-*SIGMA* decile and short positions in stocks from the lowest-*SIGMA* decile. The long-short portfolio abnormal returns are computed by forming equally weighted calendar-time portfolios of 12-month horizon and regressing the difference in portfolio returns ($R_{sigma\,10,t}$–$R_{sigma\,1,t}$) on the same four factors. The abnormal returns of each long-short portfolio are the intercepts (α_p) from the following regression:

$$R_{sigma\,10,t} - R_{sigma\,1,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t}.$$

Calendar-time portfolios are re-balanced once per year at the end of June. The estimation method is OLS. Results are presented for the July 1988 to July 2003 period. Monthly abnormal returns expressed in decimal point notation. For example, an abnormal return of 0.00328 corresponds to 32.8 bps per month. The *t*-statistics (one-tail test) reporting positive statistical significance are shown in the last column and are computed from the intertemporal variation in the monthly calendar-time portfolio returns. Results are for the July 1988 to June 2003 period.

	Idiosyncratic risk decile (*SIGMA*)											
Relative short interest (RSI) half of firms with zero I/B/E/S analyst coverage	1st decile (lowest)	2nd decile	3rd decile	4th decile	5th decile	6th decile	7th decile	8th decile	9th decile	10th decile (highest)	Long-short portfolio: deciles 10−1	*t*-Statistic of long-short portfolio
All RSI values	0.00328	0.00220	0.00059	−0.00080	−0.00062	0.00150	0.00281	0.00624	0.00752	0.00941	0.00613	[0.97]
Lower RSI half	0.00461	0.00442	0.00229	0.00483	0.00251	0.00481	0.00819	0.00717	0.01003	0.01462	0.01001	[1.75]**
Upper RSI half	0.00199	−0.00032	−0.00498	−0.00317	−0.00477	−0.00237	0.00201	0.00397	−0.00049	0.00070	−0.00128	[−0.18]

*, **, *** denotes positive statistical significance at the 10% 5% and 1% levels, respectively.

Table 7
Robustness tests of long-short portfolios using analyst coverage as proxy for visibility.

This table presents robustness tests of the long-short regressions presented in Table 5. We report results for long-short regressions for firms without analyst coverage as reported by I/B/E/S. The first row presents results for the universe of firms without analyst coverage, followed by tests that sort the zero-analyst firms into below-median *RSI* and above median *RSI* groupings. In Panel A, we examine robustness across various alternative calendar-time pricing models, while maintaining the equally weighted portfolio, annual portfolio holding periods, and annual portfolio rebalancing procedure of Table 5. In Panel B, we only present the four-factor model, while varying the portfolio holding periods and frequency of portfolio rebalancing, and we also present results where the firms are weighted by the logarithm of market capitalization.

We report the long-term abnormal return of long-short (or zero-investment) calendar-time portfolios, consisting of a long position in stocks with the highest *SIGMA* decile and a short position in stocks with the lowest *SIGMA* decile. *Idiosyncratic Risk* (*SIGMA*) is the standard deviation of the excess weekly returns (firm return minus CRSP value-weighted return) computed over the prior 52 weeks (week ending defined as of Wednesday's close). The long-short portfolio abnormal returns are computed by forming calendar-time portfolios of either 12-month horizon (both in Panels A and B) or one-month horizon (Panel B only), and regressing the difference in portfolio returns ($R_{sigma\,10,t}-R_{sigma\,1,t}$) on four-factor, five-factor, Fama/French three-factor, CAPM, and Raw return models: The five-factor model augments the four-factor model with the *LMH* liquidity risk factor, factor of Eckbo and Norli (2005), where *LMH* is the monthly difference in returns between low and high liquidity firms. In Panel A, we utilize equally weighted portfolios, while in Panel B we utilize both equally and log-of-market-capitalization-weighted portfolios. The abnormal return for each sub-sample is the intercept, (α_p) from the following regression (five factor model shown):

$$R_{sigma\,10,t} - R_{sigma\,1,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + 1_p UMD_t e_{p,t}.$$

For Panel A, we repeat the Table 5 process where calendar-time portfolios are re-balanced once per year at the end of June, and the results are for the July 1988 to June 2003 period. In Panel B, in addition to the annual rebalancing and holding period method of Panel A, we also explore: (1) one-month holding periods with monthly rebalancing and (2) 12-month holding periods with monthly rebalancing, where results of (1) and (2) are presented for the February 1988 to December 2002 periods. The estimation method is OLS. An abnormal return of 0.00613 below is to be interpreted as an abnormal return of 61.3 bps per calendar month. The *t*-statistics (one-tail test) reporting positive statistical significance are shown in brackets beside the intercepts and are computed from the intertemporal variation in the monthly calendar-time portfolio returns. For expositional convenience, the first columns of both Panel A and Panel B (four-factor results) restate long-short-portfolio results from Table 5.

Panel A: Alternative asset pricing models

Relative short interest (*RSI*) group	Asset pricing model									
	4-factor		5-factor		3-factor		CAPM		Raw returns	
	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic
All *RSI* values	0.00613	[0.97]	0.01092	[1.76]*	0.00452	[0.75]	0.00101	[0.17]	0.01324	[1.48]*
Lower *RSI* half	0.01001	[1.75]**	0.01283	[2.32]**	0.01087	[1.96]**	0.00832	[1.45]*	0.01852	[2.25]**
Upper *RSI* half	−0.00128	[−0.18]	0.00385	[0.54]	−0.00268	[−0.39]	−0.00689	[−0.98]	0.00576	[0.59]

Table 7 (*continued*)

Panel A: Alternative asset pricing models

Relative short interest (*RSI*) group	Asset pricing model									
	4-factor		5-factor		3-factor		CAPM		Raw returns	
	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic

Panel B: Alternative rebalancing periods, investment horizons, and portfolio weighting

Relative short interest (*RSI*) group	Portfolio weighting method											
	Equally weighted						Log-value-weighted					
	Rebalancing frequency											
	Annual		Monthly		Monthly		Annual		Monthly		Monthly	
	Investment horizon											
	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic	Ab. Ret.	*t*-Statistic
All *RSI* values	0.00613	[0.97]	0.00305	[0.47]	0.00377	[0.52]	0.01314	[1.93]*	0.01027	[1.46]	0.01037	[1.36]
Lower *RSI* half	0.01001	[1.75]**	0.01170	[1.98]**	0.01248	[1.77]**	0.01564	[2.32]**	0.01794	[2.70]***	0.01756	[2.36]***
Upper *RSI* half	−0.00128	[−0.18]	−0.00572	[−0.82]	−0.01143	[−1.40]	0.00784	[1.01]	0.00292	[0.39]	−0.00254	[−0.30]

*, **, *** denotes positive statistical significance at the 10% 5% and 1% levels, respectively.

Fama–MacBeth regressions of returns on continuous visibility metrics, *RSI*, *SIGMA*, and various control variables. The results of this analysis significantly strengthen the evidence in favor of Merton's IRH.

There are at least two important advantages of the Fama–MacBeth analysis relative to the long-short-portfolio calendar-time analysis. First, the information from all firms is considered in the Fama–MacBeth framework. The long-short calendar-time portfolios compare only the lowest and highest *SIGMA* deciles. Second, the Fama–MacBeth method easily incorporates additional risk factors and control variables into the cross-sectional analysis.

Our regressions deviate slightly from Fama and MacBeth's original method in that we use continuous variables rather than portfolio grouped variables. However, the following results are also evident using portfolio groupings. In the following tests, for each firm we measure future equally weighted raw returns for the one-month holding period. Each month, these future raw returns are regressed on continuous proxies for visibility, short-sale constraint, idiosyncratic volatility, as well as several control variables that are related to the cross-section of stock returns. These right-hand side variables are all measured at $t = 0$. The regression loadings are averaged intertemporally (across all months in the sample), and the results are presented in Table 8.

Column (1) of Table 8 presents results from the following specification:

$$ret_{i,t+1} = \alpha_0 + \alpha_1 IO_t + \alpha_2 RSI_t + \alpha_3 SIGMA_t + \alpha_4 MERTON\_DUMMY_t \times \alpha_5 (MERTON\_DUMMY * SIGMA)_t + \varepsilon_t. \tag{3}$$

The continuous variables used are as follows: *IO*, the proportion of shares held by institutions, *RSI* is the *relative short interest* for the firm, our proxy for dispersion of opinion. *SIGMA* is the idiosyncratic risk of the firm. Because each of these three variables is interrelated in Merton's (1987) hypothesis, we create an interaction term to capture the marginal effect of *SIGMA* when firms otherwise reside in the Merton space. Because interactions of three variables makes the coefficient estimate difficult to interpret, we construct the variable *MERTON_DUMMY* that is equal to 1 if the firm is both in the lowest three quartiles of *IO* and the lower half of *RSI*, and equal to zero otherwise. We include *MERTON_DUMMY* both as a stand-alone variable and also interacted with *SIGMA*. The stand-alone variable ensures that the coefficient of the interaction term conveys information about the effect of *SIGMA* on stock returns over the Merton region of the security space.

The coefficient of interest in the above regression is α_5, which is the marginal impact of *SIGMA* on returns when visibility and *RSI* are both low. In Column (1) of Table 8, the coefficient on this interaction term is positive and statistically significant at better than the 1% level. This result conforms to Merton's IRH.

The model used in Column (2) of Table 8 incorporates several additional control variables. *LOG_SIZE* is the logarithm of the firm's market capitalization, *B/M* is the book-to-market ratio of the firm, *PRIOR_RET* is the prior year raw holding period return (momentum), and *ILLIQUIDITY* is the Amihud (2002) illiquidity measure of the firm.[14]

[14] In this section, our Fama–MacBeth results are presented using Amihud's illiquidity measure as opposed to the turnover-based measure embedded in the LMH factor. For robustness, we verify that our results (untabulated) remain substantially unchanged when *turnover* is used in place of the Amihud measure. We present this section's results using Amihud's metric since this proxy is more commonly used in Fama–MacBeth regressions.

Table 8
Fama-Macbeth regressions.

We employ the Fama and Macbeth (1973) procedure to examine the cross-sectional relation between firm-specific returns and idiosyncratic risk, while also controlling for visibility, *relative short interest* levels, size, book/market, prior momentum, and illiquidity.

We estimate raw firm-specific holding period returns for one-month horizons for all firms. For the Fama/Macbeth procedure, the following four OLS regression models are estimated for each calendar month ($n = 180$ months), where all returns are regressed onto ex ante independent variables:

$$\text{Model 1}: \; ret_{i,t+1} = \alpha_0 + \alpha_1 IO_t + \alpha_2 RSI_t + \alpha_3 SIGMA_t + \alpha_4 MERTON\_DUMMY + \alpha_5 (MERTON\_DUMMY * SIGMA)_t + \varepsilon_t.$$

$$\text{Model 2}: ret_{i,t+1} = \alpha_0 + a_1 IO_t + \alpha_2 RSI_t + \alpha_3 SIGMA_t + \alpha_4 MERTON\_DUMMY + \alpha_5 (MERTON\_DUMMY * SIGMA)_t + \alpha_6 LOG\_SIZE_t + \alpha_7 B/M_t + \alpha_8 PRIOR\_RET_t + \alpha_9 ILLIQUIDITY_t + \varepsilon_t.$$

$$\text{Model 3}: \; ret_{i,t+1} = \alpha_0 + \alpha_1 NO\_ANALYSTS_t + \alpha_2 RSI_t + \alpha_3 SIGMA_t + \alpha_4 MERTON\_DUMMY + \alpha_5 (MERTON\_DUMMY * SIGMA)_t + \alpha_t.$$

$$\text{Model 4}: \; ret_{i,t+1} = \alpha_0 + \alpha_1 NO\_ANALYSTS_t + \alpha_2 RSI_t + \alpha_3 SIGMA_t + \alpha_4 MERTON\_DUMMY + \alpha_5 (MERTON\_DUMMY * SIGMA)_t + \alpha_6 LOG\_SIZE_t + \alpha_7 B/M_t + \alpha_8 PRIOR\_RET_t + \alpha_9 ILLIQUIDITY_t + \varepsilon_t.$$

Where, $ret_{i,t+1}$ is the holding period return of the firm, measured during the one-month following portfolio formation. The continuous variables used are as follows: *IO* (Institutional Ownership), the proportion of shares held by institutions, used as a visibility proxy in Models 1 and 2. *NO_ANALYSTS*, a dummy equal to 1 if the firm has zero analyst coverage on I/B/E/S and equal to zero otherwise, also used as a visibility proxy in Models 3 and 4. *RSI* is the *Relative Short Interest* for the firm, our proxy for dispersion of opinion. *SIGMA* is the standard deviation of the excess weekly returns (firm return minus CRSP value weighted return) computed over the prior 52 weeks (week ending defined as of Wednesday's close). *LOG_SIZE* is the logarithm of the firm's market capitalization, *B/M* is the book-to-market ratio of the firm, *PRIOR_RET* is the prior year raw holding period return (momentum), and *ILLIQUIDITY* is the Amihud (2002) illiquidity measure of the firm.

We expect the Merton effect to hold for the intersection of low visibility and low *RSI*—we thus construct the dummy variable *MERTON_DUMMY*. For Models 1 and 2, *MERTON_DUMMY* is equal to 1 if the firm is both in the lowest three quartiles of *IO* and the lower half of *RSI*, and equal to zero otherwise. In Models 3 and 4, *MERTON_DUMMY* is equal to 1 if the firm has both no analyst coverage and is in the lower half of *RSI*, and is equal to zero otherwise.

The time series averages of the regression coefficients are also reported. The interacted variables are reported with one-tailed *t*-statistics testing for positive statistical significance. Statistical significance for all other variables is considered using two-tailed tests.

Variable	Model			
	(1)	(2)	(3)	(4)
Intercept	0.01321 [4.73]***	0.05653 [6.34]***	0.01545 [4.79]***	0.06085 [7.17]***
IO	0.00350 [0.88]	0.01113 [4.08]***		
NO_ANALYSTS			−0.00098 [−0.46]	−0.00622 [−3.62]***
RSI	−0.09133 [−5.17]***	−0.07797 [−4.50]***	−0.11627 [−5.71]***	−0.07979 [−4.01]***

Table 8 (*continued*)

Variable	Model			
	(1)	(2)	(3)	(4)
SIGMA	−0.04390 [−0.79]	−0.13347 [−2.81]***	−0.03143 [−0.58]	−0.12275 [−2.64]***
MERTON_DUMMY	−0.00096 [−0.49]	−0.00698 [−3.62]***	−0.00258 [−0.83]	−0.00815 [−2.85]***
MERTON_DUMMY∗SIGMA	0.10731 [3.87]***	0.10618 [4.13]***	0.10683 [2.73]***	0.11263 [3.27]***
LOG_SIZE		−0.00333 [−5.36]***		−0.00333 [−5.24]***
B/M		0.00186 [2.72]***		0.00197 [2.85]***
PRIOR_RET		0.00677 [3.53]***		0.00704 [3.63]***
ILLIQUIDITY		−0.00020 [−1.13]		−0.00012 [−0.75]
Avg. adj. RSQ	0.03429	0.04736	0.03381	0.04755

*, **, *** denotes positive statistical significance at the 10% 5% and 1% levels, respectively.

The IL measure is estimated for each firm over the previous 250 days, using the following model:

$$IL_{i,t} = \frac{1}{D_t}\sum_{d=1}^{D_t} |R_{i,d}|/VOL_{.i,d}.$$

Here, $|R_{i,d}|$ is the absolute value of the daily percentage return for firm i on day d, $\mathrm{VOL}_{i,d}$ is the total dollar trading volume (no. shares times price) for firm i on day d, in millions USD, and D_t equals the number of trading days of non-zero volume. High values of IL denote illiquidity. The results in Column (2) are qualitatively identical to those reported in Column (1). We conclude that *SIGMA* is positively correlated with returns for firms in the Merton space, even after controlling for the usual asset-pricing factors.

The models in Columns (3) and (4) of Table 8 are identical to those in Columns (1) and (2), except that the *IO* visibility metric is now replaced by *NO_ANALYSTS*. This variable equals unity when the firm lacks sell-side analyst coverage in IBES; zero otherwise. For these regressions, the *MERTON_DUMMY* is unity for firms with no analysts and below median *RSI*. We hypothesize that the coefficient on *MERTON_DUMMY∗SIGMA* will be positive. For both models (3) and (4), we find that the point estimate of this interaction is positive and statistically significant, consistent with Merton's IRH.

In untabulated tests, we repeat the analysis in Table 8 with idiosyncratic risk (*SIGMA*) computed from the Fama–French–Carhart four-factor model instead of the excess returns. The results are almost identical to those shown in Table 8.

We also repeat the entire Fama–MacBeth analysis using a holding period equal to one year instead of one month. The regressions are still performed monthly, resulting in overlapping returns. We correct for the resulting cross-correlation using the Newey–West procedure (Newey and West, 1987). The results (untabulated) are qualitatively similar to those reported in the table. We also examine additional specifications and find that the inclusion or deletion of various combinations of control variables does not change the sign or level of significance for coefficient of interest. In addition, results remain unchanged when the monthly portfolio returns are value-weighted with the log of the market capitalization of each stock.

6. Summary and conclusions

Merton (1987) presents an "IRH" which extends the standard CAPM model under the assumption that investors only hold securities whose risk and returns characteristics they are familiar with. Because these investors hold under-diversified portfolios, they demand compensation for idiosyncratic risk. Accordingly, ex post returns are positively related to firms' idiosyncratic risk.

Direct tests of Merton's predicted positive correlation between idiosyncratic risk and returns are relatively rare. Those which have been undertaken have concluded that stocks with high idiosyncratic volatility have "abysmally low average returns", an opposite conclusion to the implications of Merton (1987). Previous studies have noted that the low returns to idiosyncratic risk seem to be more consistent with the predictions of Miller (1977). Miller theorized that short-sale constraints will result in poor returns for stocks with high dispersion of investor opinion, an attribute known to be positively correlated with trading volatility.

We hypothesize that these previous tests of Merton (1987) fail to find that idiosyncratic risk is priced for two reasons. First, Merton's hypothesis applies only to stocks with low visibility (those stocks not "recognized" by investors). Prior studies have not explicitly controlled for visibility. Second, firms with high levels of short-selling are likely either to have high dispersion of investor opinion such that the conditions for Miller's hypothesized overvaluation are present, or to have negative information that is not yet incorporated in prices. Our tests control for both visibility and short-selling activities.

Using low institutional holdings as a proxy for low visibility, we examine firms that also have relatively low short-sales activity. These firms are unlikely to possess Miller's requisite dispersion of beliefs and are also unlikely to have negative information that is not immediately priced. Using the calendar-time portfolio approach, we compare the returns of high volatility firms against firms with low volatility. We find idiosyncratic risk is priced for the least-shorted half of stocks belonging to the lowest three quartiles of IO. In other words, idiosyncratic risk appears to be priced for an economically significant fraction of U.S. stocks.

These findings are robust to alternative asset pricing model specifications, alternative portfolio weighting methods, alternative rebalancing frequencies, and alternative investment horizons. Each of these findings is qualitatively replicated when we consider the lack of sell-side analyst coverage, rather than low IO, as the indicator of low visibility.

For robustness, we also conduct a set of cross-sectional Fama–MacBeth regressions of monthly portfolio returns using alternative visibility metrics. Consistent with the calendar-time approach, the Fama–MacBeth regressions reveal that idiosyncratic risk is priced for low visibility firms that are not subject to high levels of short selling, again with high levels of statistical significance. The regression results hold whether visibility is proxied using IO or the lack of analyst coverage.

Thus, except where firms possess high visibility (inconsistent with Merton's assumptions) or where firms have high short selling (consistent with Miller's requisite dispersion of beliefs), we find that idiosyncratic risk is priced in accordance with the IRH forwarded by Merton (1987).

Acknowledgments

We thank Avanidhar Subrahmanyam and an anonymous referee for very helpful comments. This paper has also benefited from the comments of Fred Arditti, Ying Duan, Mark Flannery, Gang Hu, David McLean, Jeff Pontiff, Anna Scherbina, John Scruggs, Matt Spiegel, Mark Walker, Stephen C. Vogt of Mesirow Financial, Kevin Mirabile of ORCA Asset Management, as well as seminar participants at Texas A&M University, the University of Kansas, Wichita State University, and the 2006 Western Finance Association. Data on analysts' forecasts was provided by I/B/E/S Inc., under a program to encourage academic research.

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